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Structural Disruption, Relational Experimentation, and Performance in Professional Hockey Teams: A Network Perspective on Member Change

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Abstract. This paper explores how action teams reorganize their interdependent relationships following the exit of a key team member. To do so, I adopt a network perspective to conceptualize interaction patterns as a network, first to identify members who are central to the team's workflow, and second to assess changes in tie formation as teams experiment with their relational structure following member exit. Using data on professional hockey teams—where unexpected member change due to injury is frequent, but highly interdependent teams nonetheless carry out complex, time-sensitive work—results indicate that the injury of central players negatively affects team performance, even when controlling for individual performance. Teams adapted to central exits by maintaining their existing interaction patterns, even though higher levels of relational experimentation following an injury were positively associated with performance. By considering changes in ties within a team, a network approach focuses on the relationships that are disrupted by compositional change and provides a more flexible way of thinking about adaptation and reorganization beyond a team's formal structure.

Keywords: teams • networks • interdependence • adaptation • performance • member change

Introduction

Changes in the nature of work mean that organizational and group membership is becoming increasingly dynamic. Lifetime employment in an organization or job is increasingly rare (Arthur and Rousseau 1996, Bidwell and Briscoe 2010), and technology is affording new forms of organizing that blur organizational, group, and team boundaries (Faraj and Xiao 2006, Levine and Prietula 2013). Groups and teams commonly experience disruptions to their membership, for instance due to downsizing, promotion, and retirement. Frequent or temporary forms of member change are typical when labor is organized around shifts (Goodman and Leyden 1991) or projects (Huckman and Staats 2011). For action teams—teams that engage in complex, time-limited work that requires collective skill (Sundstrom et al. 1990)—changes in membership can be particularly disruptive because interdependent relationships are critical for performance, particularly in important areas such as patient care (Huckman and Pisano 2006, Reagans et al. 2005) and public safety (Bigley and Roberts 2001).

Thus, achieving resilient performance—maintaining function when faced with change (Allenby and Fink 2005, Weick and Sutcliffe 2007)—for many teams is both a challenge and a priority. Much of the research to address this problem has focused on preexisting structures and capabilities that allow teams to act flexibly when adaptation is required. For instance, some teams

depend on formal role structures and routines (Bechky 2006, Faraj and Xiao 2006, Klein et al. 2006) that enable members to act swiftly with unfamiliar teammates. Teams also rely on informal coordination mechanisms (Okhuysen and Bechky 2009, Bechky and Okhuysen 2011) that develop through shared experience. As such, we have a good understanding of what teams can proactively do to foster resilience in teams. We know less, however, about the reactive approaches that teams can pursue, as much of the literature on groups and teams investigates stable environments where member composition is constant (Arrow et al. 2000, McGrath 1991). Understanding how teams reactively respond to membership change can yield important insights on the tactics that teams are likely to employ and whether they are effective, and has the potential to inform a broader literature on adaptation in teams.

This paper explores how action teams reorganize due to the unexpected exit of a key team member. To do so, I adopt a network perspective to conceptualize team interaction patterns as a network. Because work in action teams requires highly specialized collective skill, a network perspective recognizes the most critical resource for the functioning of these teams: the interdependent relationships within the team itself. This is an inherently different approach than considering individual or team-level factors that are unable to capture the structure of relationships among team

members. Conceptualizing team interaction patterns provides insight on which members have the potential to disrupt team functioning and whether subsequent changes to relational structures in teams are effective.

The empirical setting for this study is a sample of National Hockey League (NHL) teams that experienced unexpected member change due to player injury. Scholars have commonly investigated sports teams to gain insight into team and organizational dynamics (e.g., Bloom 1999, Day et al. 2012, Gould and Gatrell 1979). In particular, professional hockey teams provide a unique opportunity to study member change and adaptation. First, the teams are highly interdependent in that the quality of task work and game outcomes depends on the collective contributions of all members. Second, player injuries circumvent many difficulties associated with studying changes in membership because they are an instance of change that is unexpected and independent of other factors commonly related to mobility, such as managerial decision making and individual or team performance. Third, teams experience considerable variation in task-related interaction among players.¹ Finally, measures of interdependence can be linked to objective, game-level data on player injuries, team performance, and individual performance—all necessary components to investigate the relationship between member change, networks, and team adaptation.

Member Change and Performance in Action Teams

Teams that carry out their work in action contexts are a particularly useful case for better understanding how teams adapt to member change—the entry and exit of individuals from groups or teams (Ziller 1965)—because they have a heightened need to rely on each other to complete their tasks. Action teams engage in specialized work that is carried out during temporally bounded performance episodes (Sundstrom et al. 1990), such as games for sports teams and surgeries for medical teams. Because action teams work under time constraints, they need to reliably and quickly organize the sequence and timing of their tasks, and improvise when circumstances are uncertain. One way these teams are able to react quickly is through their reliance on formal coordination mechanisms, such as roles, that help coordinate interdependent action between individuals (Okhuysen and Bechky 2009). For instance, medical trauma teams use formal, disciplinary roles such as anesthesiologist, nurse, and surgeon to flexibly coordinate their task work by treating the role occupants interchangeably based on who is available with the required expertise (Faraj and Xiao 2006). Action teams also use routines to perform reliably, and developing these routines involves extensive preparation in advance of performance episodes. Sports teams regularly practice before games, orchestras rehearse

between performances, and firefighters use simulations to train. Preexisting formal mechanisms, like roles and routines, help action teams adapt to change because they create a necessary foundation that promotes stability when plans, the environment, or membership changes.

In addition to formal coordination mechanisms, action teams also rely on emergent forms of coordination (Okhuysen and Bechky 2009) to manage the reciprocal dependencies that exist among members. Emergent coordination mechanisms arise from informal, ad hoc action and are used to respond to unplanned contingencies and rapidly changing circumstances, such as when existing procedures are insufficient to deliver patient care in trauma centers (Faraj and Xiao 2006) or when formal structures are too slow to coordinate disaster relief (Majchrzak et al. 2007). The capacity for teams to engage in informal coordination practices arises from existing team resources (Bechky and Okhuysen 2011). One particular type of existing team resource is a history of task-related interaction among interdependent individuals. For instance, a key condition necessary for coordination is the ability to predict the actions of others (Okhuysen and Bechky 2009, Mathieu et al. 2000), which is often fostered by familiarity that is acquired through direct experience working together. Similarly, the ability for team members to achieve a common understanding of a task, and each other's contributions to that task, can arise through interaction surrounding role negotiation and the formulation of plans (Bechky 2006, Bechky and Okhuysen 2011). Thus, interdependent relationships are often imbued with a history that provides the capacity for emergent coordination practices.

Changes in team membership can affect performance in action contexts because they can disrupt both formal and informal coordination mechanisms. Routines, for instance, are affected when an exiting member is replaced with someone who is less familiar with the people, processes, or equipment associated with their new position (McGrath 1991). Member change also affects the nature of relationships between members (Goodman and Leyden 1991). Correspondingly, the broader literature on member change in teams (e.g., Argote et al. 1995, Goodman and Leyden 1991, Lewis et al. 2007, Summers et al. 2012) largely suggests that membership change is disruptive to team performance (see Choi and Thompson 2005 and Kane et al. 2005 for some exceptions).

This paper focuses on the structure of interdependent relationships in teams to better understand how team performance and adaptation is affected by changes in composition. Given that interdependence is a defining feature of teams (Alderfer 1977, Hackman 1990), the pattern of these relationships could yield

new insights as to when changes in membership challenge resilient team performance, and whether adjustments to this structure can promote subsequent adaptation. For action teams, whose success is predicated on the collective skill of its members, reassessing how human capital is organized after a compositional change could be a tactic critical to maintaining consistent performance. In the next section, I suggest that a member's central position within a team's network of interdependent relationships is a potential source of vulnerability. I then discuss one particular response to member change, relational experimentation, and propose that it can mitigate the negative performance effects of changes in team membership.

A Network Perspective on Member Change

Scholars have long acknowledged that the structure of interaction and communication underlies many group processes and outcomes (Bavelas 1950, Homans 1950, Leavitt 1951). A social network perspective is particularly applicable to the research of teams because it is fundamentally about the connections among people, as opposed to the actions of individuals in isolation. The particular types of interpersonal connections that researchers measure are diverse, ranging from social relations (siblings, friends), to interactions (advice, helping), to flows (information, resources, beliefs) (Borgatti et al. 2009). This study complements past research on team networks by focusing on a less-studied set of interactions that can be captured by network analysis: the pattern of interaction among members actively carrying out interdependent work. These interactions, or interdependence ties, are shaped by the organization's workflow and stem from both formal aspects of the organization's structure and informal interactions among team members. In action teams, these types of ties are typically dictated by the formal roles and routines that are used to script performance episodes. Doctors and nurses, for instance, know how to interact with each other during a surgical procedure because of a preexisting and well-defined role structure (cf. Bechky 2006, Faraj and Xiao 2006). Some action teams develop routines through extensive training or practice that guides interaction patterns, such as military teams and orchestras. These formal aspects of the work environment provide the boundaries that members operate within to negotiate, and if necessary improvise, their interactions to carry out their work.

Interdependence is an inherently relational phenomenon that can vary across team members within teams. For instance, police officers interact more with their partners than the other officers in their division and know more about their partner's habits, preferences, and abilities. Much of the literature concerning changes in membership, however, has focused on

either the attributes of the member or team in explaining its implications for performance. From the perspective of the member, researchers have investigated how individual attributes, such as competence (Pfeffer and Davis-Blake 1986, Summers et al. 2012), influence team outcomes. The team perspective considers the impact of team-level factors such as team processes (Summers et al. 2012), emergent states (Kane et al. 2005), and routines (Rao and Argote 2006). A primary premise of this paper is that by considering the variety of interdependent relationships that exist across team members, at least two insights emerge. The first relates to an individual member's position in the team's network. Ties that capture interdependent relationships indicate the magnitude of disruption when any particular member leaves. The second relates to the overall structure of interdependence ties at the level of the team. Mapping this configuration provides insight on how teams dynamically adjust their internal relationships after a disruption, and how these changes may affect team performance.

Centrality and Performance

To help understand how changes in team composition influence performance in action teams, this paper focuses on central team members, those who have a high degree of involvement with others (Wasserman and Faust 1994). There are multiple ways to assess network centrality (Borgatti and Everett 2006, Freeman 1978), and each measures a substantively different type of contact that an actor has with others. This study focuses on degree centrality (Freeman 1978)—the number of ties that an actor has with others—to capture the number of members affected, or the magnitude of disruption, when an individual leaves a team.

Interdependence ties are particularly critical in action teams because they influence coordination in at least two ways. First, members who are central in the team's network of interdependent action accumulate relationship-specific knowledge about many different team members. This knowledge—about each other's preferences, tasks, and roles—improves coordination among people who fulfill distinct purposes (Reagans et al. 2005) by reducing the need for direct communication and allowing members to tailor their own actions in anticipation of each other's work (Okhuysen and Bechky 2009). Second, practices might develop that are particular to that interdependent relationship. Two team members, for example, might come up with shared codes and other communication shortcuts to express ideas quickly under time constraints. These shortcuts, however, are only interpretable by the two members who developed them and are not viable for use with another member. Thus, even though dyads are embedded within a broader team, the resources embedded in dyadic ties are idiosyncratic to that relationship (Reagans et al. 2005).

Empirical evidence is consistent with the idea that longstanding, interdependent relationships enhance performance in teams. For instance, when miners worked with less familiar coworkers, they were more prone to accidents (Goodman and Garber 1988) and less productive (Goodman and Leyden 1991). In a study of surgeons conducting joint-replacement surgery, those who had more experience working together completed the procedure more quickly (Reagans et al. 2005). Similarly, surgeries by cardiovascular surgeons were associated with lower mortality rates when they worked at hospitals with more familiar colleagues (Huckman and Pisano 2006).

The complexities inherent in a central member's ties, in that they have many different partners with whom they interact with in unique ways, make adjusting to a central exit challenging. Replacing these members may be insufficient because substitutes lack the relationship-specific knowledge to immediately coordinate their work with their other team members. Accordingly, teams may not be able to insert a replacement into the exiting member's network position and maintain the same level of performance. A more complex set of adjustments likely need to take place, and to adapt effectively, the team may need to engage in multiple activities—such as redistributing and reprioritizing tasks, and modifying the structure of work across a number of individuals. Due to these extensive changes, team performance may be immediately compromised as members adjust to new processes before being able to work on the task at hand (Hollingshead et al. 1993).

In summary, performance in action teams hinges on the relationships that exist between members, precisely because the capacity for coordination, in part, depends on task-related interaction. Central members, with their high connectivity to others, present a threat to team performance because their exit disrupts the team's ability to coordinate its work. Thus, even when holding individual performance constant, the departure of a central team member is expected to negatively affect team performance.

Hypothesis 1. *As the centrality of the exiting member increases, the greater the negative effect on subsequent team performance.*

Relational Experimentation and Adaptation

Organizational decision makers, such as managers and even team members themselves, devise a team's relational structure to capitalize on the team's existing composition. The challenge posed by changes in membership is that it can make these structures outmoded. One approach to address this disruption is to engage in practices that promote further change (Hedberg et al. 1976, Starbuck 1983), such as experimentation. Experimentation, a trial-and-error process where repeated iterations produce new insights on a problem (Lee et al.

2004, Thomke 1998), is central to solving problems when information is missing or outcomes are uncertain (Lee et al. 2004). The process of taking a course of action, and observing its outcomes, can lead to learning that guides future action (Weick 1998, Moorman and Miner 1998). Even when an experiment fails, it rules out one potential solution and narrows the options for future trials.

While experimentation is often discussed in terms of scientific discovery and technological advancement (e.g., Thomke et al. 1998), a similar trial-and-error approach can be applied when trying to come up with the optimal configuration of interdependent actors. Relational experimentation in teams occurs when organizational decision makers trial different combinations of members when carrying out the team's work. By creating new interdependence ties between members, decision makers can quickly cycle through different relational configurations and gain insight on how best to organize the team. Given the difficulty in predicting team performance based on the attributes of a team and its members (Woolley et al. 2010), adopting a trial-and-error approach to team composition could be a strategy that yields fruitful insights.

Teams, however, may avoid experimentation for a variety of reasons. First, experimentation inherently involves failure, which organizations and their members tend to avoid (Weick and Sutcliffe 2007). Failures reveal gaps in knowledge and expertise (Lee 1997), which can make experimentation unlikely in organizations where failure is discouraged (Cannon and Edmondson 2005). The perceived costs of experimentation may be further heightened when a team is experiencing change involving a central member, in that it may increase perceptions of scrutiny and the team's sensitivity to failure.

Second, a subset of the literature on adaptation, in particular concerning surprises in organizations, suggests that teams would avoid relational experimentation when adjusting to significant disruptions. When teams are forced to adapt under tight time constraints, they tend to leverage preexisting team resources (Bechky and Okhuysen 2011). For instance, teams make use of shared knowledge about each other's activities and the team's work, which allows them to reorder their work and adjust their routines (Bechky and Okhuysen 2011). To be able to leverage commonly held knowledge in response to a significant disruption, teams need to default to a system of interaction that is familiar to its members.

By maintaining existing ties, teams can also leverage their preexisting role structures. Groups and teams often rely on stable, interpersonal structures to maintain reliable performance when work is temporary, conditions are unpredictable, and membership changes. For instance, film crews rely on formalized

role structures to organize their work across temporary projects (Bechky 2006). Role-based systems also allow trauma teams to coordinate specialized expertise, even when the composition of the team is changing (Faraj and Xiao 2006). Accordingly, a team may strive to maintain an existing structure, because it provides a stable foundation that allows them to adapt to changing circumstances (Klein et al. 2006).

In summary, when organizational decision makers perceive a significant disruption—such as the exit of a prominent member who is central in the team’s network—they are likely to avoid relational experimentation for at least two reasons. The first reason is due to a heightened sensitivity to failure. The second is that maintaining a stable structure allows the team to leverage existing team resources, such as commonly held knowledge and role structures, that can be useful when adapting to change. For these reasons, when a central member exits, teams may avoid experimenting with new configurations and rely on their existing relational structure to carry out their work.

Hypothesis 2. *As the centrality of the exiting member increases, the team’s relational experimentation following the exit decreases.*

While teams may be reluctant to engage in relational experimentation in response to a central member’s exit, its use, nonetheless, may improve team performance. As previously noted, reconfiguring a team following membership change can be challenging. Decision makers need to consider whether interaction partners have complementary expertise; and even when two or more members are a good match in theory, other individual attributes such as personality (Barrick et al. 1998) or status (Bendersky and Hays 2012, Groysberg et al. 2011) make it hard to know whether the pairing will be functional in practice. Engaging in relational experimentation following a member’s exit may mitigate some of these challenges by quickly eliminating potential combinations of interaction partners, to arrive at a more suitable relational structure. For instance, theater productions trial combinations of potential members by having different actors do readings together, in addition to auditioning alone. Experimentation, by creating more ties among members, therefore quickly provides more information about different team configurations, which may lead to better performance outcomes (Eisenhardt 1989).

Hypothesis 3. *Following a team member exit, an increase in experimentation is positively associated with team performance.*

Methodology

Research Setting

To test these hypotheses, this study examines member change in professional hockey teams in the National Hockey League (NHL). Professional hockey teams provide an excellent opportunity to study member change and adaptation in teams for at least three reasons. First, hockey teams are a prototypical example of an action team, in that they operate as an interdependent system, develop collective skill, and coordinate their action in uncertain situations (Sundstrom et al. 1990). Second, hockey teams frequently experience changes in composition due to player injury, providing abundant instances of unexpected member change. Finally, similar to many sports organizations, the NHL records objective, fine-grained data on both individual and team performance that are free from peer and manager bias that can creep into subjective performance measures.

Hockey is a highly interdependent sport in that players are reliant on one another to achieve team objectives. Even when players are not visibly interacting (for instance by passing the puck to each other), they are still coordinating their position and movement on the ice to create passing opportunities, make space for each other to skate, and distract the opposition. The interdependent nature of the game is reflected in how hockey leagues measure individual offensive performance. Goals scored are attributed to individual players, but additionally assists—the last two consecutive players to touch the puck before the goal was scored—are tracked and weighted equally as a measure of individual performance.

While hockey players are dependent on each other to carry out their work, there is nonetheless variation among players in terms of who they interact with during a game and for how long. While 19 players typically play in a game, only six are allowed on the ice at a given time. This unique attribute of hockey, that the active subgroup of players is small compared to the overall team size, imposes considerable variation in the structure of interdependence among members. This variation is magnified by the line system employed by coaches. Players engage in short, intense shifts that last for roughly 45 seconds before being relieved by a teammate. A team is structured by the coaching staff and composed of four lines of offensive players (made up of three players each) and three lines of defensive players (made up of two players each). These lines are used interchangeably throughout the game to ensure that five skaters (plus a goaltender) are on the ice at all times. These lines often change during a game and throughout the season based on a number of factors including player performance and injuries.

Coaches also organize players based on skill: better players play more during a game and tend to be

grouped together on the same line. Adding further complexity to the structure of interdependent relationships, hockey teams also rely on certain combinations of players to deal with particular game situations, such as when the team is playing with fewer players than the opposition (due to a penalty) or more (due to an opponent's penalty). This concept of "special teams" in hockey is akin to its application in other sports, such as when American football teams rely on a specialized subset of players during kicking plays. Not surprisingly, finding the right line combination can be challenging. As noted by NHL coach Mike Babcock, "it took us a long time to figure out where everybody fit best. There were lots of changes, new guys that we brought in that didn't fit the way we thought they were, or were better than we thought they were" (Masisak 2013).

Hockey is arguably one of the fastest team sports, and teams rely on both formal and informal forms of coordination to accomplish their time-constrained work under quickly changing circumstances. Formal roles (positions such as forward and defense) and routines (plays) provide the foundation that underpins the use of informal coordination mechanisms, such as real-time communication and predictability. Real-time communication allows players to share information about their own, and their opponents', position on the ice. Predictability between players allows them to anticipate each other's actions and interact more quickly, for instance by passing to each other without looking. Like many action teams, members of hockey teams achieve predictability by rehearsing plays together during team practice (Ishak and Ballard 2012) and shared experience playing together during games. Shared time-on-ice is particularly important because it allows players to develop relationship-specific knowledge about their teammates during game situations when the team is facing a live opponent, arousal is heightened, and unexpected events are likely.

Hockey's fast-paced and physical nature makes player injuries a constant threat to team stability. Injuries can be temporary, potentially only lasting for one game, or permanent if a player fails to return before the end of the season. When dealing with an injury, teams typically add a player to the team's lineup to replace the exiting player. In addition to replacing the injured player, the coaching staff has two broad options when adjusting the team's overall structure. The first option strives for stability by maintaining the team's existing pattern of interdependence ties. It promotes stability in that it aims to preserve the team's role structure, for instance, by directly inserting the new player into the injured player's line. This approach acts to maintain or reduce the overall number of ties in the

team, by generally keeping the current pattern of interactions between role occupants and the relative exposure that these roles have to the team's work.

The second option, which is more disruptive, is to increase the total number of connections in the team by creating new ties among members. This happens when coaches engage in relational experimentation and iterate over possible combinations of players during the game. Experimentation in hockey is often referred to as "shuffling the lines," whereby the coaching staff reorganizes the forward and defensive lines in a search for "chemistry" among players that optimizes the team's performance. Shuffling can be a proactive process, for instance when a coach tries out different line combinations at the beginning of the season, or a reactive process, such as when a coach is dissatisfied with the team's performance or needs to adapt to a change in the team's roster due to injury, trade, or suspension. Experimentation manifests itself in the network as an increase in interdependence ties, or an increase in the density of the team's network. In practice, this may mean reorganizing lines such that two players who do not usually play together, are now linemates. Experimentation therefore increases the number of interdependence ties in a team by increasing the interaction among different players on the ice.

Coaches acknowledge that in their search for new information, shuffling lines often fails. In an interview, an assistant coach with the Toronto Maple Leafs described their new lines as "an experiment" and said that he was not confident that the configuration would necessarily stick (Hornby 2010). During the 2014 Winter Olympic games, the coach of the Canadian team reshuffled the team's lines throughout the tournament but only produced one line that consistently scored goals (Duhatschek 2014). When the new mix does not produce the desired results, coaches will make additional changes during the game or even revert back to the old configuration.

Data and Sample

The sample for this study consists of players who were injured in the 2006–2007 NHL regular season. Player and game data were collected from the archives on the NHL's official website (www.nhl.com) and supplemented with player injury data from the Sports Network (TSN) (www.tsn.ca). To be included for analysis, an injury met three criteria. First, the injured player missed one or more games due to his injury. Second, the player participated in 7 of the 10 games prior to his injury. This cut-off ensured that the exiting member was a stable part of the team and that dependencies had developed between him and his teammates before his injury. It also meant that there were sufficient player data before an injury to calculate measures of the player's past performance and position in the

team's network. Third, the injured player held a skating position on the team (forward or defense). Goal-tenders were removed from the sample because they are structurally unique in that they typically play the entire game, making them the most central player on a team. Because their network position is largely confounded with their formal role, goaltenders were also excluded from the team's network when calculating team network measures. Employing these inclusion criteria yielded a final sample of 601 injuries.

On average, a player missed 6.636 games ($SD = 9.145$) when injured, and roughly a quarter of these injuries lasted eight games or longer. The likelihood of a player getting injured was associated with a few different factors. The number of injuries a player experienced over an 82-game season was significantly correlated with the player's average ice time per game ($r = 0.225$, $p < 0.001$), penalties per game ($r = 0.155$, $p < 0.001$), and goals and assists per game ($r = 0.199$, $p < 0.001$). Thus, the likelihood of injury is related to opportunity (time-on-ice), exposure to rough play (penalties), and offensive skill (goals and assists). There is also a considerable range in the number of injuries that a team experienced in a season. Concerning the injuries in the final sample, teams had anywhere from 12 (Anaheim Ducks) to 32 (Chicago Blackhawks) injury events ($M = 16.433$, $SD = 5.763$). Teams also tended to experience more injuries depending on who they played. Opponents of the Chicago Blackhawks had the most injuries with 28, whereas opponents of the Boston Bruins experienced the fewest at 9.

The final sample of injuries was matched with game-level data, making the unit of analysis the injury-game. More specifically, each injury was matched with game-level data for the seven games preceding the injury (control period) and up to five games following the injury (postinjury period). This data structure allowed for the estimation of a change in team performance, before and after the injury event. Seven games are used as the length of the control period to estimate the team's performance trend leading up to the injury and captures approximately two to three weeks of team play. Model parameters were also consistent in magnitude and direction when both the control period and the postinjury period were lengthened or shortened, as described in more detail in the results section.

Postinjury games were only included in the sample when the player was unable to play. That is, if the player returned to the team in fewer than five games, his reentry signaled the end of the injury period. Accordingly, the number of postinjury games ranged between one and five. Given this time window of 7 games preceding the injury and up to 5 games including and following the injury, the total number of game observations per injury ranged between 8 and 12. The final sample consisted of 6,110 injury-game observations.

Measures

Team Performance. *Team performance* was measured using team points per game. The NHL awards points for each regular season game, depending on its outcome: two points are awarded for a win and zero points for a loss. A team is awarded one point when the score is tied after regulation time and the team later lost in overtime or a shootout. Team points was chosen as a measure of team performance over goals scored for a few reasons. First, team points are a meaningful metric for team performance because they determine the qualification and seeding of the 16 teams that make the league playoffs at the end of the season. As such, teams are incentivized to win or tie games, as opposed to winning games by a large spread of goals. Second, certain team actions are inconsistent with the idea that teams strive to win by as many goals as possible. For instance, when teams have large leads they may not play their top players and use the game as an opportunity to develop less experienced players. Third, team points are less likely to reflect the contributions of a single particularly influential player or event. For example, a performance measure such as goals for or against could be heavily skewed based on the performance of a goaltender in a particular game.

Member Change. The dummy variable *injury* is used to estimate the effect of a player's injury on team performance and network structure. It switches from zero to one for the first full game the player missed due to injury and estimates the change in the level of team performance when a player leaves his team.

Centrality. Time-on-ice data for each game were used to calculate centrality measures for injured players prior to their exit. Time-on-ice statistics track when, and for how long, each player was on the ice and were used to determine which players were on the ice together and how long their shifts overlapped. Similar to other empirical studies of social networks that rely on proxies to infer the existence of a tie between individuals (Borgatti and Halgin 2011), this study assumes that players who are on the ice together interact and function in an interdependent manner. For two players to have a "tie," they must have been on the ice together for at least 138 seconds during a game (approximately three shifts). This cutoff ensures that the overlap between players is deliberate and not due to brief interactions during line changes. This relatively low cutoff also ensures that player interaction due to special teams (such as the power play and penalty kill), which may be infrequent, is also captured. Player centrality was calculated using Freeman's (1978) measure of degree centrality, defined as the number of direct ties one player on the team has to all other players on the team,

$$C_D = \frac{d}{g-1},$$

where d is the number of nodes to which a focal node is connected and g is the number of nodes in the network. Thus, a player's centrality is calculated using information from team-level interaction patterns. Centrality was calculated for every game in the preinjury period, and the average of these observations was used to create the member *centrality* measure.

Operationalizing Relational Experimentation. To capture *team experimentation* in response to member change, this paper relied on one property of networks, density. Team density measures the total number of ties in the network divided by the number of possible ties (Iacobucci 1994),

$$D = \frac{T}{(g(g-1))/2},$$

where T is the total number of ties in the team network and g is the number of members on the team. Values of density can range between zero and one, where a value of one indicates that all team members are connected to each other. Density broadly captures the relational configuration of a hockey team, in that it measures the extent of contact between different players. Teams with a dense structure have many ties between their members, meaning that players interact with each other to a more similar extent. Teams with a sparse structure have fewer ties among members. As with the centrality measure, time-on-ice data were used to calculate team density for each game. The practice of experimentation is observed in the team's network as an increase in density—the number of shared interaction ties in the games following member change. Interaction among different players increases in dense teams, in that players play with more teammates.

To test Hypothesis 3, the variable *experimentation change* was created to measure an increase or decrease in experimentation when a player became injured. *Experimentation change* is a team's density in the game following a player's injury, minus the team's average density in the seven games preceding the injury. Accordingly, positive values for *experimentation change* indicate that a team increased its density following a player's injury. A negative value indicates that a team decreased the number of ties among players, relative to the period preceding the injury.

Control Variables. To address factors that may affect team performance, other than network position and structure, the following time-varying, team-level controls were calculated. *Team past performance* is the total number of points earned to date by a team in that season, divided by the total number of games played. Similarly, *opponent past performance* captures the average number of points earned by the opposing team up to the focal game. The variable *home team* is one when the team is playing at its home rink and zero when the

team is playing at an opponent's arena. It controls for the potential advantage of playing in a familiar arena with supportive fans. To control for multiple injuries in the same game, *team injuries* is a count of the total number of players who are currently injured in the focal game.

Two controls were also created to capture recent player performance. *Player points* is the average number of individual points scored by the injured player (goals plus assists) for each game in the seven-game preinjury period. An additional measure for player performance is *player time-on-ice (TOI)*, which is the amount of time a player actively plays in a game and better captures the value of defensive players who may not accumulate many goals or assists. Central players also tend to have higher TOI, and controlling for TOI rules out the alternative explanation that a relationship between centrality and performance (or experimentation) is instead caused by player TOI. Player TOI is constructed in the same manner as the player past performance variable.

Empirical Strategy

The empirical aim of this study is to examine whether an exiting member's centrality influences team performance, the team's adaptation in response to that exit, and whether the nature of the adaptation affects team performance. To do so, this study relies on player injuries to estimate changes in team performance and network structure after a team's composition is disrupted. Isolating the specific effect of member exit on team performance and adaptation in a field setting is difficult because employee mobility is often due to a number of individual, team, and organizational factors. One way to overcome these confounds is to study instances of member change that are independent of managerial decision making or individual ability, such as unplanned entry and exit from teams. As such, player injury serves as an unexpected shock to the team's composition and can be used to isolate the impact of member change on team performance and adaptation. While injuries themselves are common in hockey, the timing of an injury to a particular player is unexpected as coaches do not select which player becomes injured or at what point during the season. A similar empirical approach has been employed in the literature on scientific production, where scientist death has been used as an exogenous change in a coauthoring relationship to identify the effect of star coauthors (Azoulay et al. 2010), and helpful colleagues (Oettl 2012), on individual production.

As previously mentioned, to estimate changes in team performance and network structure before and after an injury, the model makes use of the indicator variable *injury* that switches from zero to one in the first full game that the player missed due to injury. When the outcome of interest is team performance, for instance,

injury estimates the team's deviation from their average performance preceding the injury. The variable *centrality* is interacted with *injury* to estimate the effect of the injured player's network position on the team's change in performance from their preinjury level. Likewise, *experimentation change* is interacted with *injury* to estimate the relationship between a change in relational experimentation and team performance.

The model also includes a fixed effect for every injury event, meaning that the regression parameters can be interpreted as the effect of an injury on within-team performance change (as opposed to estimating whether this effect varies across teams). Relatedly, the injury fixed effect acts to partial out the unobserved time-invariant attributes related to the player injury, including attributes of the player (such as physical size and severity of the injury) and attributes of the team (such as coaching staff ability). An opponent fixed effect was also included to control for time-invariant attributes related to the opposing team (such as the coaching staff). The injury and opponent fixed effects also account for the fact that, as previously mentioned, certain teams were more susceptible to injury, and that playing certain teams was associated with a greater chance of injury occurrence.

A few steps were taken to address multiple sources of nonindependence among observations. First, the inclusion of the injury fixed effect accounts for nonindependence due to the nesting of game-level observations within injuries, because the parameters are estimated from within-group variance. Second, all models report robust standard errors that are robust to within-group correlation (such as serially correlated game observations; Wooldridge 2000). A remaining source of nonindependence is at the player level. Some players are injured more than once in the season, meaning that the residuals for injuries that concern the same player are correlated. To address this concern, standard errors are clustered at the player, to correct for the nonindependence among some injury observations.

Results

The aim of this research is to answer three main questions. First, does the effect of a member's exit on team performance depend on that member's centrality? Second, how do teams adjust their structures in response to a central exit? Third, what is the impact of this adaptation on team performance? Tables 1 and 2 report the descriptive statistics and correlations among study variables. While player points (a conventional measure of player performance) is positively correlated with centrality, centrality is more strongly associated with time-on-ice during games, suggesting why defensive players ($M = 0.667$, $SD = 0.096$) are more central than forward ($M = 0.473$, $SD = 0.094$). Defensive players

Table 1. Descriptive Statistics

Variable	Mean	Std. dev.	Min	Max
Team performance (team points, per game)	1.075	0.934	0	2
Team past performance	1.093	0.249	0.250	2
Opponent past performance	1.104	0.237	0	2
Player points (goals and assists, preinjury average)	0.352	0.311	0	2.286
Player time-on-ice (minutes, preinjury average)	14.295	4.154	2.610	25.305
Home team	0.500	0.500	0	1
Team injuries (total, per game)	2.704	1.619	0	9
Injury game	0.311	0.463	0	1
Player centrality (preinjury average)	0.546	0.134	0.089	0.912
Team experimentation (per game)	0.542	0.046	0.353	0.712
Change in team experimentation	0.000	0.042	-0.120	0.111

Notes. This table reports the summary statistics for all variables used in the analyses. Injury-game observations: $N = 6,110$. Descriptive statistics are reported for uncentered variables.

tend to play more minutes in a game, which puts them in contact with a greater number of teammates.

Table 3 reports the results of six regression specifications that investigate the relationship between an injured player's centrality and team performance. Each model first reports the set of team and opponent control variables. The two player performance controls—*player points* and *player time-on-ice*—cannot be directly estimated in the presence of the injury fixed effect because these player attributes do not vary over time. To estimate these controls directly, these variables were centered and interacted with *injury*. Model 1 reports a baseline model that estimates the effect of any player's injury on his team's performance. Without estimating the centrality of the injured player, but controlling for the player's other attributes, the injury of any player has a positive effect on his team's performance. That the effect of any injured player is not negative is conceivable given that hockey teams are configured to withstand injuries, by having multiple players who fulfill the same position on the team bench. Results from model 1 also indicate that teams perform better when they have a history of winning more games in the season and play in their home arena. Teams perform worse when they compete against a better performing opponent and have more players injured.

Hypothesis 1—that teams experience a greater performance loss the more central the departing member—is tested in model 2 by centering *player centrality* and interacting it with *injury*. Similar to the player performance controls, the main effect for centrality cannot be directly estimated in the presence of the injury fixed effect because a player's mean centrality does not vary over time. The coefficient for the *injury* \times *centrality* interaction term is negative, consistent with Hypothesis 1, but not significant ($p = 0.210$).

Table 2. Correlations Among Variables

	1	2	3	4	5	6	7	8	9	10
1 <i>Team performance</i>	—									
2 <i>Team past performance</i>	0.263	—								
3 <i>Opponent past performance</i>	−0.256	−0.136	—							
4 <i>Player points</i>	0.016	0.066	−0.016	—						
5 <i>Player time-on-ice</i>	0.003	0.032	0.017	0.337	—					
6 <i>Home team</i>	0.103	0.002	−0.023	0.006	0.007	—				
7 <i>Team injuries</i>	−0.100	−0.172	0.062	−0.051	0.044	−0.018	—			
8 <i>Injury game</i>	−0.008	−0.006	0.023	−0.020	−0.008	0.014	0.262	—		
9 <i>Player centrality</i>	−0.015	−0.061	0.032	0.046	0.770	0.002	0.064	−0.020	—	
10 <i>Team experimentation</i>	−0.222	−0.167	0.046	−0.055	−0.029	−0.104	0.101	0.005	0.100	—
11 <i>Experimentation change</i>	0.005	0.031	0.025	−0.042	−0.030	−0.010	−0.033	0.004	0.065	−0.026

Notes. Injury-game observations: $N = 6,110$. Correlations greater than and equal to 0.026 are significant at $p < 0.05$.

Additional analyses using piecewise regression (models 3–6) were conducted to better understand the relationship between player centrality and team performance. Piecewise regression permits various linear models to be estimated over various ranges of a pre-

dictor variable, and allows for a different slope to be estimated at multiple values of the predictor. Unlike linear regression, it does not assume that the relationship between a predictor and outcome is constant for all values of the predictor. The specification reported in

Table 3. Fixed-Effects Ordinary Least Squares (OLS) and Poisson Estimates of Team Performance on Player Centrality

	(1) OLS Tie = 3 shifts	(2) OLS Tie = 3 shifts	(3) OLS Tie = 3 shifts	(4) Poisson Tie = 3 shifts	(5) OLS Tie = 2 shifts	(6) OLS Tie = 4 shifts
Dependent variable: <i>Team performance</i>						
<i>Team past performance</i>	4.686** (0.390)	4.703** (0.389)	4.705** (0.388)	5.019** (0.552)	4.704** (0.388)	4.691** (0.389)
<i>Opponent past performance</i>	−1.191** (0.106)	−1.192** (0.106)	−1.191** (0.106)	−1.067** (0.163)	−1.193** (0.106)	−1.191** (0.106)
<i>Home team</i>	0.174** (0.024)	0.174** (0.024)	0.175** (0.024)	0.167** (0.020)	0.175** (0.024)	0.175** (0.024)
<i>Team injuries</i>	−0.043** (0.014)	−0.044** (0.014)	−0.045** (0.014)	−0.039* (0.016)	−0.045** (0.014)	−0.044** (0.014)
<i>Injury</i>	0.062* (0.030)	0.078* (0.031)	0.151** (0.047)	0.105* (0.048)	0.143** (0.053)	0.111* (0.045)
<i>Injury × Player points</i>	−0.100 (0.084)	−0.148* (0.089)	−0.185* (0.092)	−0.176* (0.092)	−0.184* (0.094)	−0.146 (0.091)
<i>Injury × Player TOI</i>	0.001 (0.006)	0.014 (0.011)	0.013 (0.011)	0.010 (0.010)	0.013 (0.010)	0.010 (0.013)
<i>Injury × Centrality</i>		−0.456 (0.363)				
<i>Injury × Centrality</i> 50			0.248 (0.500)	0.201 (0.454)	0.109 (0.513)	0.080 (0.529)
<i>Injury × Centrality</i> 100			−1.083* (0.510)	−1.010* (0.464)	−0.939* (0.475)	−0.711 (0.560)
Constant	−2.449** (0.452)	−2.463** (0.451)	−2.469** (0.449)		−2.464** (0.449)	−2.453** (0.451)
Injury FE	Yes	Yes	Yes	Yes	Yes	Yes
Opponent FE	Yes	Yes	Yes	Yes	Yes	Yes
Game observations	6,110	6,110	6,110	6,110	6,110	6,110
Injury observations	601	601	601	601	601	601
R-squared	0.182	0.182	0.183		0.183	0.182
Log likelihood				−6,113		

Notes. The dependent variable in models 1–6 is the number of points earned in a game for the injured player's team. Models 1–4 define a tie between players as three overlapping shifts, model 5 as two overlapping shifts, and model 6 as four overlapping shifts. Models 1–3, 5, and 6 are estimated using OLS regression with robust standard errors clustered at the player reported in parentheses. Model 4 is estimated using Poisson regression with bootstrapped standard errors (100 replications) reported in parentheses. All regressions include fixed effects for each injury (partialled out) and each opponent. The injury window for all models includes seven games leading up to an injury and five games following the injury.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

model 3 incorporates two parameters that correspond to different percentile breakpoints for centrality. *Centrality*₅₀ is a continuous variable that takes the value of a player's centrality when it is below the median and is coded the sample median for players with centrality values over the median. *Centrality*₁₀₀ is coded zero when a player's centrality is below the median and is the player's centrality value when it is above the median. Correspondingly, when interacted with *injury*, the variable *centrality*₅₀ estimates the slope for all players with centrality values below the 50th percentile, and *centrality*₁₀₀ represents the slope for injured players with centrality values above the 50th percentile.

The results for model 3 suggest that centrality negatively affects team performance, but only for a particular range of values. For low-centrality players (below the 50th percentile), these injuries have no impact on team performance. At the 50th percentile of centrality, however, the relationship between centrality and performance is negative and significant ($p = 0.035$), and this change in slope at the median is significant ($b = -1.331$, $SE = 0.0705$, $p = 0.060$). For these high-centrality players, a one standard deviation increase in centrality results in a 7.26% reduction in team points per game.

Models 4–6 report specifications that investigate the robustness of these estimates. First, because the dependent variable, *team performance*, is count data with many zeros, model 4 replicates model 3 using a fixed-effects Poisson estimator as opposed to OLS. These coefficient estimates, estimated via quasi-maximum likelihood (QML), are consistent with the OLS results. Second, models 5 and 6 replicate the specification from model 3 using two alternative measures of a network tie. In model 5, two players must have played at least two on-ice shifts together in a game to have a tie between them. When centrality is calculated based on this alternative measure, results are consistent with model 3. As reported in model 6, findings are also consistent in direction when a tie is defined by an overlap of at least four on-ice shifts; however, the magnitude of the effect of player centrality on performance is smaller compared to models 3 and 5, and not significant ($p = 0.205$). Overall, these results suggest mixed findings concerning the effect of player centrality on team performance. It appears that the centrality of some members, but not all, influences team performance. Further, the effect of centrality on performance is sensitive to how centrality is calculated. An injured player's centrality is associated with team performance when the definition of a tie between players is less stringent and requires less interaction between two players (models 3 and 5). These findings may suggest that the exit of a central member is most disruptive to players with whom they interact with the least.

Hypothesis 2 predicted that an exiting member's centrality would be negatively associated with the

team's relational experimentation following the exit. Table 4 examines the effect of an injured player's centrality on team density. Consistent with the controls reported in Table 3, model 1 includes a set of team, opponent, and player control variables. In addition, the set of models reported in Table 4 controls for team points earned in each game. Doing so rules out the alternative explanation that a change in experimentation is caused by a team's poor performance, as opposed to an injured player's centrality. As indicated in models 1–5, the relationship between team performance and density is negative and significant, suggesting that when teams are performing poorly, they engage in less experimentation.

To test Hypothesis 2, *centrality* was centered and interacted with *injury* to estimate the effect of the injured player's centrality on his team's experimentation. That is, the interaction term estimates a change in a team's level of density from its preinjury average. In support of Hypothesis 2, team structure becomes less dense as the centrality of the injured member increases (model 2). This result is consistent with the idea that a central exit is negatively associated with relational experimentation. In other words, teams experiment less—by reducing the number of ties between players—when a central member becomes injured.

Model 3 explores the alternate explanation that the number of games missed by a player due to injury drives experimentation, as opposed to the player's centrality. It is possible that central players incur more severe injuries because they are higher profile or spend more time on the ice, and the length of absence influences the degree of experimentation. Model 3 reports an interaction between *injury* and *missed games* to directly test this idea. *Missed games* is the number of games the player was unable to play with his team following his injury, mean centered and divided by 10. As reported in model 3, the number of missed games associated with an injury had no effect on relational experimentation. The relationship between centrality and experimentation also remains the same with the inclusion of missed games as a control variable.

Models 4 and 5 replicate the specification from model 2 but instead define a network tie as two (model 4) and four (model 5) overlapping shifts. Results are consistent with those reported in model 2.

Table 5 reports a set of regressions that investigate Hypothesis 3, which predicted that teams would perform better following a change in membership if they engaged in experimentation. To assess whether experimentation affects team performance, *experimentation change* was centered and interacted with *injury*. A positive relationship between experimentation change and team performance would indicate that an increase in the number of ties among teammates is positively associated with team performance. Model 1 includes the

Table 4. Fixed Effects OLS Estimates of Relational Experimentation on Player Centrality

Dependent variable: <i>Relational experimentation</i>	(1) Tie = 3 shifts	(2) Tie = 3 shifts	(3) Tie = 3 shifts	(4) Tie = 2 shifts	(5) Tie = 4 shifts
<i>Team performance</i>	−0.009** (0.001)	−0.009** (0.001)	−0.009** (0.001)	−0.010** (0.001)	−0.005** (0.001)
<i>Team past performance</i>	−0.005 (0.009)	−0.002 (0.009)	−0.003 (0.009)	0.002 (0.009)	0.005 (0.008)
<i>Opponent past performance</i>	−0.016** (0.004)	−0.016** (0.004)	−0.016** (0.004)	−0.011** (0.004)	−0.011** (0.004)
<i>Home team</i>	−0.008** (0.001)	−0.008** (0.001)	−0.008** (0.001)	−0.008** (0.001)	−0.008** (0.001)
<i>Team injuries</i>	−0.001* (0.001)	−0.001* (0.001)	−0.001* (0.001)	−0.001 (0.001)	−0.001+ (0.001)
<i>Injury</i>	0.003* (0.001)	0.005** (0.002)	0.005** (0.002)	0.004** (0.002)	0.004* (0.002)
<i>Injury × Player points</i>	−0.001 (0.004)	−0.007 (0.005)	−0.007 (0.005)	−0.006 (0.004)	−0.004 (0.004)
<i>Injury × Player TOI</i>	0.000 (0.000)	0.002** (0.001)	0.002** (0.001)	0.001* (0.001)	0.001* (0.001)
<i>Injury × Centrality</i>		−0.056** (0.016)	−0.056** (0.017)	−0.047** (0.015)	−0.057** (0.018)
<i>Injury × Missed games (0s)</i>			−0.001 (0.001)		
Constant	0.594** (0.012)	0.592** (0.012)	0.593** (0.012)	0.662** (0.013)	0.494** (0.011)
Injury FE	Yes	Yes	Yes	Yes	Yes
Opponent FE	Yes	Yes	Yes	Yes	Yes
Game observations	6,110	6,110	6,110	6,110	6,110
Injury observations	601	601	601	601	601
R-squared	0.077	0.080	0.080	0.090	0.057

Notes. The dependent variable in models 1–5 is relational experimentation, which is operationalized as a team's density in a given game. Models 1–3 define a tie between players as three overlapping shifts, model 4 as two overlapping shifts, and model 5 as four overlapping shifts. Missed games is the number of games a player missed due to injury, divided by 10. All models are estimated using OLS regression and include fixed effects for each injury (partialed out) and each opposing team. The injury window for all models includes seven games leading up to an injury and five games following the injury. Robust standard errors clustered at the player are in parentheses.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

team, opponent, and player controls reported in the previous tables as well as the *injury × experimentation change* interaction term. Unlike previously reported results, the postinjury period was shortened to only include the first game that the player missed following his injury, because this is the game in which the effects of experimentation should be the most impactful. In support of Hypothesis 3, teams performed better when their structures became denser following an injury. A one standard deviation increase in ties among players is associated with an increase of roughly one-fifth of a point in that game.

Models 2 and 3 in Table 5 replicate model 1 when a tie between players is defined as two shifts and four shifts, respectively. Model 4 replicates model 1 using a fixed effects Poisson estimator. Results are consistent across models 1–4, suggesting that these findings are robust to both variations in tie construction, as well as the type of estimator.

Additional analyses were conducted to investigate whether the relationship between experimentation and team performance depends on the centrality of the injured player. Model 5 includes a three-way interaction between *injury*, *experimentation change*, and *centrality*, which is negative and significant ($p = 0.097$). Simple slopes tests (Aiken and West 1991) indicated a positive and significant association between performance and experimentation at both low (−1 SD below the mean; $b = 6.342$, $SE = 1.136$, $p < 0.001$) and high (+1 SD above the mean; $b = 3.419$, $SE = 1.409$, $p = 0.015$) values of centrality. Moreover, the association between experimentation and performance was more positive for low values of centrality than high, and this difference was significant ($b = 2.923$, $SE = 1.761$, $p = 0.097$). Therefore, the value of experimentation for team performance decreases with the centrality of the injured player. Experimentation helped team performance regardless of who was injured; however, it more

Table 5. Fixed Effects OLS and Poisson Estimates of Team Performance on Change in Experimentation

Dependent variable: <i>Team performance</i>	(1) OLS Tie = 3 shifts	(2) OLS Tie = 2 shifts	(3) OLS Tie = 4 shifts	(4) Poisson Tie = 3 shifts	(5) OLS Tie = 3 shifts
<i>Team past performance</i>	5.258** (0.549)	5.271** (0.551)	5.280** (0.548)	5.975** (0.747)	5.271** (0.548)
<i>Opponent past performance</i>	−1.034** (0.115)	−1.031** (0.114)	−1.025** (0.114)	−0.924** (0.152)	−1.034** (0.114)
<i>Home team</i>	0.174** (0.029)	0.172** (0.029)	0.177** (0.029)	0.170** (0.028)	0.174** (0.029)
<i>Team injuries</i>	−0.045* (0.018)	−0.044* (0.019)	−0.045* (0.019)	−0.040* (0.020)	−0.047* (0.018)
<i>Injury</i>	0.025 (0.039)	0.024 (0.039)	0.022 (0.040)	−0.051 (0.041)	0.066 (0.044)
<i>Injury × Player points</i>	−0.185+ (0.109)	−0.175 (0.112)	−0.182 (0.112)	−0.158 (0.118)	−0.279* (0.119)
<i>Injury × Player TOI</i>	0.003 (0.009)	0.004 (0.008)	0.001 (0.009)	0.003 (0.009)	0.029+ (0.016)
<i>Injury × Experimentation change</i>	4.697** (0.924)	4.653** (0.882)	3.105** (0.927)	5.150** (1.028)	4.949** (0.920)
<i>Injury × Centrality</i>					−0.963+ (0.506)
<i>Injury × Experimentation change × Centrality</i>					−10.936+ (6.567)
Constant	−3.341** (0.649)	−3.358** (0.651)	−3.381** (0.649)		−3.350** (0.647)
Injury FE	Yes	Yes	Yes	Yes	Yes
Opponent FE	Yes	Yes	Yes	Yes	Yes
Game observations	4,808	4,808	4,808	4,808	4,808
Injury observations	601	601	601	601	601
<i>R</i> -squared	0.196	0.196	0.193		0.198
Log likelihood				−4,555	

Notes. The dependent variable in models 1–5 is the number of points earned in a game for the injured player’s team. A network tie between two players is defined as three overlapping shifts for models 1, 4, and 5; two overlapping shifts for model 2; and four overlapping shifts for model 3. Experimentation change is operationalized as team density in the game following a player’s injury, minus the team’s average density in the seven games preceding the injury. Models 1–3 and 5 are estimated using OLS regression with robust standard errors clustered at the player reported in parentheses. Model 4 is estimated using Poisson regression with bootstrapped standard errors (100 replications) reported in parentheses. The injury window for all models includes seven games leading up to an injury and one game following the injury. Each specification includes fixed effects for each injury (partialled out) and each opposing team.

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

greatly benefited teams when their injured player was peripheral, as opposed to central, in the team’s network. This interaction is plotted in Figure 1.

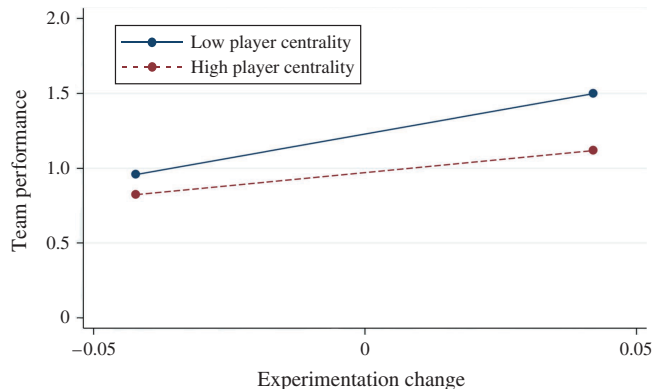
Robustness Checks

Additional analyses were conducted to assess the robustness of these primary findings. First, the lengths of the pre- and postinjury periods were varied. Results are consistent with those reported here when the preinjury period is shortened up to 4 games preceding the player’s injury and lengthened up to 10 games. The number of games following a player’s injury was also varied. Results for Hypotheses 1 and 2 are consistent when the postinjury period is expanded to include up to seven games following the injury, or shortened to include up to two games.

Second, along with the OLS and Poisson estimators that were used to test the effect of centrality and den-

sity on team performance, additional analyses were conducted using logistic regression with a categorical win/lose dependent variable. The logistic regression results are qualitatively similar, and for ease of interpretation, the OLS and Poisson regression results are reported.

In addition, and as previously mentioned, there are multiple sources of nonindependence in these data. To check that this nonindependence was not biasing these results, standard errors were generated through bootstrapping (100 iterations). Bootstrapping is a nonparametric approach that does not rely on strong assumptions about the distribution of a statistic (Guan 2003). Thus, it can be used to calculate standard errors when the error terms may not be independently distributed, as is the case with these data. Results were consistent with those reported here.

Figure 1. (Color online) Estimated Team Performance by Team Experimentation and Injured Player Centrality

Notes. Estimated team performance following player injury, for low (-1 SD) and high ($+1$ SD) values of team experimentation change and player centrality. Experimentation change is operationalized as team density in the game following a player's injury, minus the team's average density in the seven games preceding the injury.

Finally, additional variables were constructed and included as controls. Models that controlled for an injured player's position (forward versus defense) and the point in the season were consistent with those reported here.

Discussion

These results indicate three primary findings relating to networks, performance, and adaptation in action teams. First, teams experienced a drop in performance following the exit of members central to the team's interdependent work. These findings are consistent with the idea that the exit of a central member is disruptive to performance in action teams, possibly because these members hold relationship-specific knowledge necessary for coordinating interdependent, time-sensitive work. It is important to note, however, that it was not until a player reached the median value for centrality that a negative relationship between centrality and performance was observed. That is, at least in this empirical context, there exists a threshold at which a member's centrality started to pose a threat to team performance. Second, teams engaged in less relational experimentation as the centrality of the exiting member increased. Finally, the reorganization of a team's structure of interdependent relationships played a pivotal role in fostering adaptation. Teams that experimented following member change had higher performance than those that did not experiment. These findings suggest that simply replacing team members may be an insufficient adaptive response to certain changes in composition. A more functional approach might be to experiment with a range of relational configurations to find the best fit among the current members of the team.

In terms of methodology, these analyses employ a longitudinal data set on professional hockey teams, where member change is an unexpected event, and interdependence between members, individual performance, and team performance are accurately measured. Using unexpected player injuries to estimate the relationship between member change and team performance reduces the likelihood that changes in team performance result from an unmeasured variable or is confounded with attributes of the member or team. These data additionally provide a strong test of these hypotheses because studying change in networks longitudinally circumvents the causal ambiguity that arises from cross-sectional analysis. Moreover, analyses controlled for a variety of time-varying and objectively measured individual and team-level factors, along with the time-invariant attributes of the injured player and his team.

Theoretical and Practical Contributions

This study highlights a type of network tie that has unique implications for performance and adaptation. Theorizing about networks and group performance has largely focused on different types of relational ties, such as communication patterns (Cummings and Cross 2003, Leavitt 1951, Sparrowe et al. 2001), informal social relationships (Oh et al. 2004, 2006), and access to support and advice (Kane and Borgatti 2011, Kane and Labianca 2011). This paper instead focuses on the role of interdependence ties, suggesting that they help action teams coordinate their complex, time-constrained work. These findings also suggest that the exit of highly central members can negatively impact performance in action teams, possibly because they possess relationship-specific knowledge about many different team members, which makes them hard to replace. This is a different explanation for the value of central members than previously proposed; for instance, that their value stems from accessing and circulating information (e.g., Leavitt 1951).

The idea that one's position within a network of interdependence ties is critical to team performance is similar to Humphrey and colleagues' (2009) assertion that team members who occupy roles with high exposure to a team's workflow are the most critical for team performance. Members central in their team's network could also be considered to occupy a "core role," in that they interact with a large proportion of the team to carry out interdependent work. These central members, however, may not be necessarily categorized within an organization's formal structure, suggesting that for some teams, certain "core roles" may be identified by a pattern of informal relationships, as opposed to a formal position. Therefore, we may be able to glean additional insights about team member contributions by understanding a team's informal structure,

in addition to the formal structure delineated by the organization.

This study complements a rich literature concerning practices and organizational structures that promote resilient team performance (Weick and Sutcliffe 2007). SWAT teams, film crews, and emergency medical teams rely on roles, hierarchy, and practices to enable members to respond quickly to change and setbacks (Bechky 2006, Bechky and Okhuysen 2011, Klein et al. 2006). Complementing this prior research, which focused on preexisting structures or *proactive* practices that enabled teams to act flexibly, this paper focuses on relational experimentation as a *reactive* adaptive practice. These findings suggest that by engaging in relational experimentation, as opposed to relying on established interaction patterns, teams can better adapt to the exit of their members. Organizations often struggle with the loss of key members. An intuitive response to these disruptions is to replace that member with someone with similar skills and expertise; however, these findings suggest that direct replacement may not always be the optimal solution. Instead, team performance may benefit from engaging in relational experimentation following the exit of a central member. Therefore, it is important for teams to acknowledge that their pattern of interaction may be outmoded given the team's new membership and to view turnover as an opportunity to find a better relational structure given its new stock of human capital.

This study also contributes to a growing literature concerning network destabilization. Research concerning organizational downsizing and turnover has focused on the implications of the removal of a node from a network on individual-level outcomes (e.g., Shah 2000; Krackhardt and Porter 1985, 1986); however, we know less about the implications of the removal of a node for team or network-level outcomes. Some insight on this question stems from studies investigating covert and terrorist communication networks (e.g., Carley et al. 1998, Tsvetovat and Carley 2003) that are fundamentally interested in how to select a node to cease a network's functioning. This paper addresses a question that is highly pertinent to legitimate organizations. Given the removal of a node, how can a network best restructure to optimally function? These findings suggest that, notably for peripheral nodes, organizations may observe better outcomes if they experiment by cycling through different relational configurations, as opposed to inserting someone new into an empty position.

These findings also suggested two important points for teams to consider when adapting to changes in membership. First, teams were more likely to avoid experimentation when faced with the exit of a central member, even though experimentation yielded better performance outcomes. This finding is consistent with

the broader idea that individuals, groups, and organizations act less flexibly or varied under conditions of threat (Staw et al. 1981). This finding also speaks to the importance of considering psychological processes in the study of social networks (Casciaro et al. 2015), as organizational decision makers made systematic choices based on changes in the team's network. Future research could investigate, in more depth, the motivation and reasoning underlying these choices. Second, these findings also suggest that relational experimentation is more beneficial for certain types of exit. The performance gains from experimentation were greater following a peripheral exit compared to a central exit. This is consistent with the idea that as the centrality of a member increases; it becomes increasing difficult to compensate for their exit.

That experimentation is positively associated with performance raises additional questions for further investigation. Do some managers react better than others to disruptions? To what degree does the effect of experimentation depend on the ability of leaders to read the situation and time the intervention effectively? It is also possible that managers who experiment engage in other practices that promote flexibility. As previously discussed, adaptive organizations rely on structures and practices that build the team's capacity for flexible action (e.g., Bechky 2006, Faraj and Xiao 2006, Klein et al. 2006). Further research is needed to more precisely understand how the capabilities of leaders and teams interact with specific practices to allow teams to reliably perform when confronted with change.

The timing of relational experimentation as an intervention could be a potential avenue for future research. These findings suggest that experimentation is beneficial immediately following a change in membership; however, there may be other applications. For instance, experimentation might be particularly useful when teams are first forming, as there may be a greater openness to change (Wageman et al. 2009) and norms and routines are less entrenched (Tuckman 1965) compared to more longstanding teams. Also related to timing, it may not be feasible, or desirable, for all action teams to engage in experimentation during performance episodes. Across action teams, the practical implications of reliable performance vary greatly. For many, such as emergency response teams and medical teams, the potential for any decrement in performance makes experimentation a potentially undesirable intervention. All action teams, however, engage in some form of preparation or practice. Orchestras prepare for performances by rehearsing, and airline flight crews train for nonroutine events using flight simulators (Waller 1999). Thus, while it would be ill advised for some action teams to experiment during performance episodes, all action teams are able to try out different

relational configurations during practice and training sessions. From a broader standpoint, experimentation in advance of performance episodes could be viewed as a form of contingency planning, and other organizations might be able to learn from action teams by integrating contingency planning into their operations in a more systematic way.

Boundary Conditions and Limitations

It is important to consider these findings in light of potential boundary conditions. Interdependence ties capture meaningful activity in action teams that, in the case of medical teams, military teams, and cockpit crews, carry out highly consequential work. From a broader standpoint, these teams operate in fast-paced and turbulent environments, much like an increasing number of organizations (Brown and Eisenhardt 1997, Cascio 2003). Thus, while hockey teams have similar attributes to teams in a variety of organizational contexts, it is nonetheless important to consider the content of these ties before extending these findings to other types of teams. It may be more appropriate to consider other types of ties, such as communication (e.g., Bavelas 1950, Cummings and Cross 2003, Shaw 1964) or informal socializing ties (e.g., Oh et al. 2004, 2006), in other types of groups and teams.

It is also important to consider that many of these injuries were temporary absences, and players returned to their teams within a few games. This attribute of member change has little impact on the time-constrained performance of action teams because they must immediately adjust to an exit regardless of whether it is temporary or permanent. Future research, however, could investigate the reintegration of members after a temporary absence in other types of teams and how it influences the effectiveness of adaptation strategies. Gruenfeld et al. (2000) touched on this topic, and expanding work in this area could help researchers think more broadly about the different implications of temporary versus permanent absences for team adaptation and performance.

Another point to note is that this study did not investigate the attributes of replacement members. Attributes of new members affect team processes (e.g., Summers et al. 2012), and the centrality of new members in networks outside of a team (for instance the larger organization) might as well. In knowledge-based work, for instance, one could imagine that these ties could be important conduits for new information or act to bridge different parts of an organization.

Team boundaries are becoming increasingly porous to respond to task, organizational, and environmental demands. By highlighting the often dynamic nature of team composition, and investigating more flexible ways to adapt to these changes, this study aims to contribute to our understanding of change in teams and

provides a way of thinking about adaptation and reorganization beyond a team's formal structure.

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Endnote

¹This study relies on a nonproximal measure of interdependence and makes use of time-on-ice data to measure whether players are on the ice at the same time during a game and share a network tie. The underlying intuition is that when players share ice time, they are mutually dependent on one another and are working together toward a common goal.

References

- Aiken LS, West SG (1991) *Multiple Regression: Testing and Interpreting Interactions* (Sage, Newbury Park, CA).
- Alderfer CP (1977) Group and intergroup relations. Hackman JR, Suttle JL, eds. *Improving Life at Work* (Goodyear, Santa Monica, CA), 227–296.
- Allenby B, Fink J (2005) Toward inherently secure and resilient societies. *Science* 309(5737):1034–1036.
- Argote L, Insko CA, Yovetich N, Romero AA (1995) Group learning curves: The effects of turnover and task complexity on group performance. *J. Appl. Soc. Psych.* 25(6):512–529.
- Arrow H, McGrath J, Berdahl J (2000) *Small Groups as Complex Systems: Formation, Coordination, Development and Adaptation* (Sage, Thousand Oaks, CA).
- Arthur MB, Rousseau DM (1996) *The Boundaryless Career: A New Employment Principle for a New Organizational Era* (Oxford University Press, New York).
- Azoulay P, Zivin JSG, Wang J (2010) Superstar extinction. *Quart. J. Econom.* 125(2):549–589.
- Barrick MR, Stewart GL, Neubert MJ, Mount MK (1998) Relating member ability and personality to work-team processes and team effectiveness. *J. Appl. Psych.* 83(3):377–391.
- Bavelas A (1950) Communication patterns in task-oriented groups. *J. Acoustical Soc. Amer.* 22(6):725–730.
- Bechky BA (2006) Gaffers, gofers, and grips: Role-based coordination in temporary organizations. *Organ. Sci.* 17(1):3–21.
- Bechky BA, Okhuysen GA (2011) Expecting the unexpected? How SWAT officers and film crews handle surprises. *Acad. Management J.* 54(2):239–261.
- Bendersky C, Hays N (2012) Status conflict in groups. *Organ. Sci.* 23(2):323–340.
- Bidwell M, Briscoe F (2010) The dynamics of interorganizational careers. *Organ. Sci.* 21(5):1034–1053.
- Bigley GA, Roberts KH (2001) The incident command system: High-reliability organizing for complex and volatile task environments. *Acad. Management J.* 44(6):1281–1299.
- Bloom M (1999) The performance effects of pay dispersion on individuals and organizations. *Acad. Management J.* 42(1):25–40.
- Borgatti SP, Everett MG (2006) A graph-theoretic perspective on centrality. *Soc. Networks* 28(4):466–484.

- Borgatti SP, Halgin DS (2011) On network theory. *Organ. Sci.* 22(5): 1168–1181.
- Borgatti SP, Mehra A, Brass DJ, Labianca G (2009) Network analysis in the social sciences. *Science* 323(5916):892–895.
- Brown SL, Eisenhardt KM (1997) The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Admin. Sci. Quart.* 42(1):1–34.
- Cannon MD, Edmondson AC (2005) Failing to learn and learning to fail (intelligently): How great organizations put failure to work to innovate and improve. *Long Range Planning* 38(3):299–319.
- Carley KM, Reminga J, Kamneva N (1998) Destabilizing terrorist networks. Institute for Software Research, Paper 45. Accessed December 8, 2016, <http://repository.cmu.edu/isr/45>.
- Casciaro T, Barsade SG, Edmondson AC, Gibson CB, Krackhardt D, Labianca G (2015) The integration of psychological and network perspectives in organizational scholarship. *Organ. Sci.* 26(4):1162–1176.
- Cascio W (2003) Changes in workers, work and organizations. Borman W, Ilgen D, Klimoski J, eds. *Handbook of Psychology* (Wiley, Hoboken, NJ), 401–422.
- Choi H, Thompson L (2005) Old wine in a new bottle: Impact of membership change on group creativity. *Organ. Behav. Human Decision Processes* 98(2):121–132.
- Cummings J, Cross R (2003) Structural properties of work groups and their consequences for performance. *Soc. Networks* 25(3):197–210.
- Day DV, Gordon S, Fink C (2012) The sporting life: Exploring organizations through the lens of sport. *Acad. Management Ann.* 6(1): 397–433.
- Duhatschek E (2014) Canadian hockey coach Babcock will continue to tinker. *Globe and Mail* (February 17), <http://www.theglobeandmail.com/sports/olympics/canadian-hockey-coach-babcock-will-continue-to-tinker/article16920534/>.
- Eisenhardt KM (1989) Making fast strategic decisions in high-velocity environments. *Acad. Management J.* 32(3):543–576.
- Faraj S, Xiao Y (2006) Coordination in fast-response organizations. *Management Sci.* 52(8):1155–1169.
- Freeman LC (1978) Centrality in social networks conceptual clarification. *Soc. Networks* 1(3):215–239.
- Goodman PS, Garber S (1988) Absenteeism and accidents in a dangerous environment: Empirical analysis of underground coal mines. *J. Appl. Psych.* 73(1):81–86.
- Goodman PS, Leyden DP (1991) Familiarity and group productivity. *J. Appl. Psych.* 76(4):578–586.
- Gould P, Gatrell A (1979) A structural analysis of a game: The Liverpool v Manchester United Cup Final of 1977. *Soc. Networks* 2(3):253–273.
- Groysberg B, Polzer JT, Elfenbein HA (2011) Too many cooks spoil the broth: How high-status individuals decrease group effectiveness. *Organ. Sci.* 22(3):722–737.
- Gruenfeld DH, Martorana PV, Fan ET (2000) What do groups learn from their worldliest members? Direct and indirect influence in dynamic teams. *Organ. Behav. Human Decision Processes* 82(1): 45–59.
- Guan W (2003) From the help desk: Bootstrapped standard errors. *Stata J.* 3(1):71–78.
- Hackman J (1990) *Groups That Work, and Those That Don't* (Jossey-Bass, San Francisco).
- Hedberg BLT, Nystrom PC, Starbuck WH (1976) Camping on seesaws: Prescriptions for a self-designing organization. *Admin. Sci. Quart.* 21(1):41–65.
- Hollingshead AB, McGrath JE, O'Connor KM (1993) Group task performance and communication technology: A longitudinal study of computer-mediated versus face-to-face work groups. *Small Group Res.* 24(3):307–333.
- Homans GC (1950) *The Human Group* (Harcourt Brace & Co., New York).
- Hornby L (2010) Leafs shuffle lines in hopes of a spark. *Toronto Sun* (October 31), <http://www.torontosun.com/sports/hockey/2010/10/31/15899721.html>.
- Huckman RS, Pisano GP (2006) The firm specificity of individual performance: Evidence from cardiac surgery. *Management Sci.* 52(4):473–488.
- Huckman RS, Staats BR (2011) Fluid tasks and fluid teams: The impact of diversity in experience and team familiarity on team performance. *Manufacturing Service Oper. Management* 13(3): 310–328.
- Humphrey SE, Morgeson FP, Mannor MJ (2009) Developing a theory of the strategic core of teams: A role composition model of team performance. *J. Appl. Psych.* 94(1):48–61.
- Iacobucci D (1994) Graphs and matrices. Wasserman S, Faust K, eds. *Social Network Analysis: Methods and Applications* (Cambridge University Press, New York), 92–166.
- Ishak AW, Ballard DI (2012) Time to re-group: A typology and nested phase model for action teams. *Small Group Res.* 43(1):3–29.
- Kane AA, Argote L, Levine JM (2005) Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality. *Organ. Behav. Human Decision Processes* 96(1):56–71.
- Kane GC, Borgatti SP (2011) Centrality-IS proficiency alignment and workgroup performance. *MIS Quart.-Management Inform. Systems* 35(4):1063–1078.
- Kane GC, Labianca GJ (2011) IS avoidance in health-care groups: A multilevel investigation. *Inform. Systems Res.* 22(3):504–522.
- Klein KJ, Ziegert JC, Knight AP, Xiao Y (2006) Dynamic delegation: Shared, hierarchical, and deindividualized leadership in extreme action teams. *Admin. Sci. Quart.* 51(4):590–621.
- Krackhardt D, Porter LW (1985) When friends leave: A structural analysis of the relationship between turnover and stayer's attitudes. *Admin. Sci. Quart.* 30(2):242–261.
- Krackhardt D, Porter LW (1986) The snowball effect: Turnover embedded in communication networks. *J. Appl. Psych.* 71(1): 50–55.
- Lee F (1997) When the going gets tough, do the tough ask for help? Help seeking and power motivation in organizations. *Organ. Behav. Human Decision Processes* 72(3):336–363.
- Lee F, Edmondson AC, Thomke S, Worline M (2004) The mixed effects of inconsistency on experimentation in organizations. *Organ. Sci.* 15(3):310–326.
- Leavitt HJ (1951) Some effects of certain communication patterns on group performance. *J. Abnormal Psych.* 46(1):38–50.
- Levine SS, Prietula MJ (2013) Open collaboration for innovation: Principles and performance. *Organ. Sci.* 25(5):1414–1433.
- Lewis K, Belliveau M, Herndon B, Keller J (2007) Group cognition, membership change, and performance: Investigating the benefits and detriments of collective knowledge. *Organ. Behav. Human Decision Processes* 103(2):159–178.
- Majchrzak A, Jarvenpaa SL, Hollingshead AB (2007) Coordinating expertise among emergent groups responding to disasters. *Organ. Sci.* 18(1):147–161.
- Masisak C (2013) Red Wings clicking after season of figuring identity. *NHL.com* (May 19), <http://www.nhl.com/ice/news.htm?id=671298>.
- Mathieu JE, Heffner TS, Goodwin GF, Salas E, Cannon-Bowers JA (2000) The influence of shared mental models on team process and performance. *J. Appl. Psych.* 85(2):273–283.
- McGrath JE (1991) Time, interaction, and performance (TIP): A theory of groups. *Small Group Res.* 22(2):147–174.
- Moorman C, Miner AS (1998) Organizational improvisation and organizational memory. *Acad. Management Rev.* 23(4):698–723.
- Oettl A (2012) Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Sci.* 58(6):1122–1140.
- Oh H, Chung M-H, Labianca G (2004) Group social capital and group effectiveness: The role of informal socializing ties. *Acad. Management J.* 47(6):860–875.
- Oh H, Labianca G, Chung M-H (2006) A multilevel model of group social capital. *Acad. Management Rev.* 31(3):569–582.
- Okhuysen GA, Bechky BA (2009) Coordination in organizations: An integrative perspective. *Acad. Management Ann.* 3(1):463–502.
- Pfeffer J, Davis-Blake A (1986) Administrative succession and organizational performance: How administrator experience mediates the succession effect. *Acad. Management J.* 29(1):72–83.

- Rao RD, Argote L (2006) Organizational learning and forgetting: The effects of turnover and structure. *Eur. Management Rev.* 3(2): 77–85.
- Reagans R, Argote L, Brooks D (2005) Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Sci.* 51(6):869–881.
- Shah PP (2000) Network destruction: The structural implications of downsizing. *Acad. Management J.* 43(1):101–112.
- Shaw M (1964) Communication networks. Berkowitz L, ed. *Advances in Experimental Social Psychology* (Academic Press, New York), 111–147.
- Sparrowe RT, Liden RC, Wayne SJ, Kraimer ML (2001) Social networks and the performance of individuals and groups. *Acad. Management J.* 44(2):316–325.
- Starbuck WH (1983) Organizations as action generators. *Amer. Sociol. Rev.* 48(1):91–102.
- Staw BM, Sandelands LE, Dutton JE (1981) Threat rigidity effects in organizational behavior: A multilevel analysis. *Admin. Sci. Quart.* 26(4):501–524.
- Summers JK, Humphrey SE, Ferris GR (2012) Team member change, flux in coordination, and performance: Effects of strategic core roles, information transfer, and cognitive ability. *Acad. Management J.* 55(2):314–338.
- Sundstrom E, De Meuse KP, Futrell D (1990) Work teams. *Amer. Psychologist* 45(2):120–133.
- Thomke SH (1998) Managing experimentation in the design of new products. *Management Sci.* 44(6):743–762.
- Thomke S, Von Hippel E, Franke R (1998) Modes of experimentation: An innovation process—and competitive—variable. *Res. Policy* 27(3):315–332.
- Tsvetov M, Carley KM (2003) Bouncing back: Recovery mechanisms of covert networks. *North Amer. Assoc. Comput. Soc. Organ. Sci. (NAACSOS) Conf. Proc.*, Pittsburgh.
- Tuckman B (1965) Developmental sequence in small groups. *Psych. Bull.* 63(6):384–99.
- Wageman R, Fisher CM, Hackman JR (2009) Leading teams when the time is right: Finding the best moments to act. *Organ. Dynam.* 38(3):192–203.
- Waller MJ (1999) The timing of adaptive group responses to nonroutine events. *Acad. Management J.* 42(2):127–137.
- Wasserman S, Faust K (1994) *Social Network Analysis: Methods and Applications* (Cambridge University Press, New York).
- Weick KE (1998) Introductory essay—Improvisation as a mindset for organizational analysis. *Organ. Sci.* 9(5):543–555.
- Weick KE, Sutcliffe KM (2007) *Managing the Unexpected* (Wiley, San Francisco).
- Wooldridge JM (2000) *Introductory Econometrics: A Modern Approach* (South-Western, Cincinnati).
- Woolley AW, Chabris CF, Pentland A, Hashmi N, Malone TM (2010) Evidence for a collective intelligence factor in the performance of human groups. *Science* 330(6004):686–688.
- Ziller RC (1965) Toward a theory of open and closed groups. *Psych. Bull.* 64(3):164–182.

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